

# Current Trends in Image Similarity Search and application in Fashion based Image Search Engine

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In this paper we have studied various traditional and current trends in use of artificial intelligence in Image Similarity Search. It explores and implements multiple state-of-the-art methodologies to develop an alternative to Google Lens, focusing on fashion-specific applications like cosplay recognition. The proposed approaches encompass feature extraction using pre-trained convolutional neural networks (ResNet, VGG, EfficientNet), deep metric learning through Siamese Networks and Triplet Loss, embeddings generated by Vision Transformers (ViTs) and CLIP, hashing-based retrieval methods such as Locality Sensitive Hashing (LSH), and latent space mappings via autoencoder architectures.

To train and evaluate these methods, a custom cosplay image dataset was created by scraping a wide range of cosplay pictures from the internet. Images were categorized into separate folders representing distinct classes, enabling robust training of the different models. Fine-tuning and performance evaluation of the models were conducted using metrics such as precision, recall, and retrieval accuracy, with particular emphasis on computational efficiency and scalability for real-time usage scenarios.

Through comparative analysis, this study identifies the strengths and limitations of each technique, providing insights into their suitability for various use cases in fashion-focused image search, from high-speed retrieval systems to scenarios demanding high accuracy and robustness. The findings highlight effective solutions for advancing image similarity search technologies in fashion and related domains.

Additional Key Words and Phrases: Image Similarity Search, Deep Metric Learning, Vision Transformers,

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## 1 Introduction

### 1.1 Background

Introducing Image Similarity Search, the problems of Image Retrieval on the basis of Image Content, Product etc.

### 1.2 Objective

State the aim of the paper, which is to review and analyze recent advancements in SLAM techniques, compare their performance, and identify future research directions.

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### 1.3 Scope

The scope of this report is to understand

## 2 Literature Review

As noted in the introduction, this report covers a wide range of models and techniques for the problem of image similarity search.

Methods used in this problem include, - Feature extraction using pre-trained convolutional neural networks (CNNs) like ResNet[4], VGG[13], or EfficientNet[14], followed by nearest neighbor search (e.g., k-NN or cosine similarity).

- Deep metric learning approaches such as Siamese Networks or Triplet Loss-based models[6]

- Visual embeddings generated via Vision Transformers (ViTs)[1] or CLIP.

- Hashing-based methods such as Locality Sensitive Hashing (LSH) or deep learning-based hashing

- Autoencoder-based image reconstruction to map images into a latent space for similarity comparison.

Other papers/models read: [1] [2] [3] [4] [5] [6] [7] [9] [8] [10] [11] [12] [13] [14] [15] [16] [17]

## 3 Methodology

### 3.1 Dataset

### 3.2 Architecture

In the following report we have implemented and tested the following models falling under various different categories.

**3.2.1 Traditional Features.** Features like SIFT, SURF and ORB are extracted for all the images as a feature list. After that, K-Nearest Neighbour with KDTree and L2 are trained on the feature list.

**3.2.2 Pre-trained Deep learning Models.** Models like ResNet, VGG, MobileNet and EfficientNet are used to extract and store a feature list of the dataset images. After that, K-Nearest Neighbour with KDTree and L2 are trained on the feature list.

**3.2.3 Pre-trained Vision Transformers.** Models like Google's Vision Transformer, CLiP are used to extract vision features of the training images and stored in a feature list. After that, K-Nearest Neighbour with KDTree with euclidian distance metrics are trained on the feature list.

**3.2.4 Deep Metrics.** Models with the methodology of a Siamese Network with Triplet Loss is used to extract vision features of the training images and stored in a feature list. After that, K-Nearest Neighbour with KDTree and L2 are trained on the feature list.

### 3.3 Testing

To test the models, the Caltech 101 dataset is segmented using a text classifier model to classify the different classes into parent classes.

Out of every child class, we have extracted 3-4 images at random and made predictions on them.

During the predictions we keep track of metrics like nDCG, Recall, mAP (Precision) and Retrieval Time of the models predictions and the average scores for the models are reported for the overall dataset.

4 Comparative Analysis

4.1 Performance Metrics

Define and explain common performance metrics used to evaluate SLAM algorithms, such as accuracy, computational efficiency, robustness, and scalability.

4.2 Benchmarks and Datasets

Discuss popular benchmarks and datasets used for evaluating SLAM techniques (e.g., KITTI, TUM RGB-D, EuRoC MAV).

4.3 Comparison of Techniques

Quantitative Comparison: Present a table comparing different SLAM methods based on performance metrics. Qualitative Comparison: Discuss strengths and weaknesses of each method, real-world applicability, and typical use cases.

4.4 Results

Table 1. Performance Metrics for Image Similarity Models

Model	Precision	Recall	nDCG	Retrieval Time (s)
ResNet	0.84	1.00	0.93	0.10
EfficientNet	0.90	1.00	0.95	0.07
VGG	-	-	-	-
MobileNet	-	-	-	-
ViT	-	-	-	-
CLiP	-	-	-	-
Siamese Network	-	-	-	-
SN w/LSH	-	-	-	-
Autoencoder	-	-	-	-

Model training time: 30 Mins for both models.

5 Challenges and Limitations

5.1 Environmental Challenges:

Discuss challenges posed by different environments (e.g., dynamic environments, large-scale environments, featureless environments).

5.2 Sensor Limitations

: Address limitations of different sensors (e.g., sensitivity to lighting conditions, range limitations).

5.3 Computational Challenges

: Discuss the computational demands of SLAM algorithms and the trade-offs between accuracy and efficiency.

6 Recent Advances and Trends

6.1 Deep Learning in SLAM

Review how deep learning techniques are being integrated into SLAM for feature extraction, place recognition, and more.

6.2 Real-Time SLAM

Discuss advancements in making SLAM algorithms real-time capable.

6.3 Robust SLAM

Explore techniques aimed at increasing the robustness of SLAM in challenging conditions.

7 Future Directions

7.1 Integration with AI:

Discuss potential for further integration of AI and machine learning with SLAM.

7.2 Improved Sensor Fusion:

Explore opportunities for better combining data from multiple sensors.

7.3 Scalability:

Address the need for SLAM systems to handle larger and more complex environments.

7.4 Standardization:

Highlight the importance of creating standardized benchmarks and evaluation protocols for SLAM.

8 Conclusion

Summarize key findings, restate the significance of SLAM in various fields, and underscore the importance of continued research and development to overcome current limitations and meet future demands.

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